Kuisioner Penelitian

Responden yang terhormat:

Kami adalah mahasiswa jurusan manajemen **Universitas Katolik Widya Mandala** yang sedang melakukan penelitihan tentang *Analisa Pengaruh Faktor Ukuran Toko, Konfigurasi toko, dan Lokasi Terhadap Pertimbangan Konsumen dalam Mengunjungi Hypermart East Coast Center Surabaya*. Segala informasi yang Anda berikan semata-mata digunakan untuk kegiatan ilmiah. Atas kerjasama yang diberikan, kami mengucapkan banyak terima kasih.

Screening Responden:

1. Saudara pernah mengunjungi Hypermart *East Coast Center* Surabaya dalam satu bulan terakhir (Oktober 2011).
   a. ya b. tidak
   (jika tidak, mohon tidak dilanjutkan pengisian kuesioner)

Data Identitas Responden

Jenis kelamin:

□ Laki-laki Perempuan

(pilih salah satu jawaban dengan memberikan tanda silang pada kotak pilihan)

Status marital:

□ Single Menikah

(pilih salah satu jawaban dengan memberikan tanda silang pada kotak pilihan)

Umur saudara saat ini: ___________ tahun

Status Saudara:

□ Pelajar/mahasiswa Wiraswasta
□ Pekerja swasta Profesional (dokter, dll)
□ Ibu Rumah Tangga Lain-lain

Rata-rata pengeluaran per bulan:

□ < 1 juta 1 juta – < 3 juta
□ 3 juta - < 5 juta ≥ 5 juta

Tempat tinggal anda saat ini:

a. Surabaya Utara
b. Surabaya Selatan
c. Surabaya Timur
d. Surabaya Barat
e. Surabaya Pusat
f. Luar Surabaya

Petunjuk pengisian
Untuk pernyataan-pernyataan berikut merupakan penilaian terhadap Hypermart *East Coast Center* Surabaya. Berikan penilaian anda dengan memberi tanda silang (X) pada salah satu angka yang paling sesuai dengan pilihan anda. berikut ini adalah keterangan dari setiap nomor:

1= Sangat tidak setuju **2.= Tidak setuju** **3= Cukup setuju**
4 = Setuju **5= Sangat setuju**

Ukuran Toko

NO	Pertanyaan	1	2	3	4	5
1	Besar kecilnya Hypermart dilihat dari jauh dekatnya lokasi, menjadi pertimbangan anda untuk mengunjungi Hypermart.					
2	Besar kecilnya Hypermart dilihat dari kemudahan akses menuju toko, menjadi pertimbangan anda untuk mengunjungi Hypermart.					
3	Besar kecilnya Hypermart dilihat dari strategisnya lokasi (dekat dengan berbagai fasilitas umum, perbankan, perkantoran, dan lainnya), menjadi pertimbangan anda untuk mengunjungi Hypermart.					

Komposisi Retail

NO	Pertanyaan	1	2	3	4	5
1	Sedikit banyaknya komposisi produk di Hypermart dilihat dari jauh dekatnya lokasi, menjadi pertimbangan anda untuk mengunjungi Hypermart.					
2	Sedikit banyaknya komposisi produk di Hypermart dilihat dari kemudahan akses menuju toko, menjadi pertimbangan anda untuk mengunjungi Hypermart.					
3	Sedikit banyaknya komposisi produk di Hypermart dilihat dari strategisnya lokasi (dekat dengan berbagai fasilitas umum,					

	perbankan, perkantoran, dan lainnya), menjadi pertimbangan anda untuk mengunjungi Hypermart.					

Citra Retail / Layanan

NO	Pertanyaan	1	2	3	4	5
1	Baik buruknya citra layanan Hypermart dilihat dari jauh dekatnya lokasi, menjadi pertimbangan anda untuk mengunjungi Hypermart.					
2	Baik buruknya citra layanan Hypermart dilihat dari kemudahan akses menuju toko, menjadi pertimbangan anda untuk mengunjungi Hypermart.					
3	Baik buruknya citra layanan Hypermart dilihat dari strategisnya lokasi (dekat dengan berbagai fasilitas umum, perbankan, perkantoran, dan lainnya), menjadi pertimbangan anda untuk mengunjungi Hypermart.					

Terima kasih

Lampiran 2. Profile Responden

Jenis Kelamin Responden

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Laki-Laki	52	52,0	52,0	52,0
	Perempuan	48	48,0	48,0	100,0
	Total	100	100,0	100,0	

Status Responden

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Single	44	44,0	44,0	44,0
	Menikah	56	56,0	56,0	100,0
	Total	100	100,0	100,0	

Usia Responden

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-23 tahun	22	22,0	22,0	22,0
	24-29 tahun	36	36,0	36,0	58,0
	30-35 tahun	28	28,0	28,0	86,0
	> 35 tahun	14	14,0	14,0	100,0
	Total	100	100,0	100,0	

Pekerjaan Responden

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Pelajar/mahasiswa	9	9,0	9,0	9,0
	Wiraswasta	31	31,0	31,0	40,0
	Pekerja swasta	39	39,0	39,0	79,0
	Profesional	5	5,0	5,0	84,0
	Ibu Rumah Tangga	16	16,0	16,0	100,0
	Total	100	100,0	100,0	

Pengeluaran Per Bulan

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	< 1 juta	7	7,0	7,0	7,0
	1 juta - < 3 juta	62	62,0	62,0	69,0
	3 juta - < 5 juta	23	23,0	23,0	92,0
	5 juta ke atas	8	8,0	8,0	100,0
	Total	100	100,0	100,0	

Tempat Tinggal

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Surabaya Utara	39	39,0	39,0	39,0
	Surabaya Selatan	13	13,0	13,0	52,0
	Surabaya Timur	35	35,0	35,0	87,0
	Surabaya Barat	11	11,0	11,0	98,0
	Surabaya Pusat	2	2,0	2,0	100,0
	Total	100	100,0	100,0	

Lampiran 3. Uji Validitas dan Reliabilitas

Correlations

Correlations

		Besar kecilnya Hypermart-jauh dekatnya lokasi	Besar kecilnya Hypermart -kemudahan akses	Besar kecilnya Hypermart -strategisnya lokasi	Total1
Besar kecilnya Hypermart-jauh dekatnya lokasi	Pearson Correlation	1	,599**	,535**	,814**
	Sig. (2-tailed)		,000	,000	,000
	N	100	100	100	100
Besar kecilnya Hypermart-kemudahan akses	Pearson Correlation	,599**	1	,639**	,863**
	Sig. (2-tailed)	,000		,000	,000
	N	100	100	100	100
Besar kecilnya Hypermart-strategisnya lokasi	Pearson Correlation	,535**	,639**	1	,878**
	Sig. (2-tailed)	,000	,000		,000
	N	100	100	100	100
Total1	Pearson Correlation	,814**	,863**	,878**	1
	Sig. (2-tailed)	,000	,000	,000	
	N	100	100	100	100

**. Correlation is significant at the 0.01 level (2-tailed).

Reliability

Case Processing Summary

		N	%
Cases	Valid	100	100,0
	Excluded[a]	0	,0
	Total	100	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
,803	3

Correlations

Correlations

		Sedikit banyaknya komposisi produk -jauh dekatnya lokasi	Sedikit banyaknya komposisi produk -kemudahan akses	Sedikit banyaknya komposisi produk -strategisnya lokasi	Total2
Sedikit banyaknya komposisi produk -jauh dekatnya lokasi	Pearson Correlation	1	,616**	,438**	,831**
	Sig. (2-tailed)		,000	,000	,000
	N	100	100	100	100
Sedikit banyaknya komposisi produk -kemudahan akses	Pearson Correlation	,616**	1	,574**	,866**
	Sig. (2-tailed)	,000		,000	,000
	N	100	100	100	100
Sedikit banyaknya komposisi produk -strategisnya lokasi	Pearson Correlation	,438**	,574**	1	,804**
	Sig. (2-tailed)	,000	,000		,000
	N	100	100	100	100
Total2	Pearson Correlation	,831**	,866**	,804**	1
	Sig. (2-tailed)	,000	,000	,000	
	N	100	100	100	100

**. Correlation is significant at the 0.01 level (2-tailed).

Reliability

Case Processing Summary

		N	%
Cases	Valid	100	100,0
	Excluded[a]	0	,0
	Total	100	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
,777	3

Correlations

Correlations

		Baik buruknya citra layanan -jauh dekatnya lokasi	Baik buruknya citra layanan -kemudahan akses	Baik buruknya citra layanan -strategisnya lokasi	Total3
Baik buruknya citra layanan -jauh dekatnya lokasi	Pearson Correlation	1	,772**	,655**	,893**
	Sig. (2-tailed)		,000	,000	,000
	N	100	100	100	100
Baik buruknya citra layanan -kemudahan akses	Pearson Correlation	,772**	1	,761**	,933**
	Sig. (2-tailed)	,000		,000	,000
	N	100	100	100	100
Baik buruknya citra layanan -strategisnya lokasi	Pearson Correlation	,655**	,761**	1	,889**
	Sig. (2-tailed)	,000	,000		,000
	N	100	100	100	100
Total3	Pearson Correlation	,893**	,933**	,889**	1
	Sig. (2-tailed)	,000	,000	,000	
	N	100	100	100	100

**. Correlation is significant at the 0.01 level (2-tailed).

Reliability

Case Processing Summary

		N	%
Cases	Valid	100	100,0
	Excluded[a]	0	,0
	Total	100	100,0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
,890	3

Lampiran 4. Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,642
Bartlett's Test of Sphericity	Approx. Chi-Square	419,453
	df	36
	Sig.	,000

Anti-image Matrices

		Besar kecilnya Hypermart-jauh dekatnya lokasi	Besar kecilnya Hypermart -kemudahan akses	Besar kecilnya Hypermart -strategisnya lokasi	Sedikit banyaknya komposisi produk -jauh dekatnya lokasi	Sedikit banyaknya komposisi produk -kemudahan akses	Sedikit banyaknya komposisi produk -strategisnya lokasi	Baik buruknya citra layanan -jauh dekatnya lokasi	Baik buruknya citra layanan -kemudahan akses	Baik buruknya citra layanan -strategisnya lokasi
Anti-image Covariance	Besar kecilnya Hypermart-jauh dekatnya lokasi	,441	-,201	-,081	,204	-,030	-,069	,073	-,067	,024
	Besar kecilnya Hypermart-kemudahan akses	-,201	,406	-,215	-,114	-,072	,131	-,044	,042	-,055
	Besar kecilnya Hypermart-strategisnya lokasi	-,081	-,215	,536	,036	,016	-,086	,008	-,031	,020
	Sedikit banyaknya komposisi produk -jauh dekatnya lokasi	,204	-,114	,036	,425	-,194	-,107	,075	-,076	,080
	Sedikit banyaknya komposisi produk -kemudahan akses	-,030	-,072	,016	-,194	,457	-,222	,020	-,025	,009
	Sedikit banyaknya komposisi produk -strategisnya lokasi	-,069	,131	-,086	-,107	-,222	,577	-,112	,074	-,025
	Baik buruknya citra layanan -jauh dekatnya lokasi	,073	-,044	,008	,075	,020	-,112	,357	-,179	-,042
	Baik buruknya citra layanan -kemudahan akses	-,067	,042	-,031	-,076	-,025	,074	-,179	,259	-,168
	Baik buruknya citra layanan -strategisnya lokasi	,024	-,055	,020	,080	,009	-,025	-,042	-,168	,379
Anti-image Correlation	Besar kecilnya Hypermart-jauh dekatnya lokasi	,613[a]	-,476	-,166	,470	-,068	-,136	,185	-,197	,060
	Besar kecilnya Hypermart-kemudahan akses	-,476	,592[a]	-,461	-,275	-,166	,270	-,115	,129	-,140
	Besar kecilnya Hypermart-strategisnya lokasi	-,166	-,461	,753[a]	,076	,033	-,154	,018	-,083	,045
	Sedikit banyaknya komposisi produk -jauh dekatnya lokasi	,470	-,275	,076	,532[a]	-,441	-,217	,193	-,230	,199
	Sedikit banyaknya komposisi produk -kemudahan akses	-,068	-,166	,033	-,441	,648[a]	-,433	,050	-,074	,023
	Sedikit banyaknya komposisi produk -strategisnya lokasi	-,136	,270	-,154	-,217	-,433	,548[a]	-,246	,191	-,054
	Baik buruknya citra layanan -jauh dekatnya lokasi	,185	-,115	,018	,193	,050	-,246	,690[a]	-,590	-,115
	Baik buruknya citra layanan -kemudahan akses	-,197	,129	-,083	-,230	-,074	,191	-,590	,631[a]	-,537
	Baik buruknya citra layanan -strategisnya lokasi	,060	-,140	,045	,199	,023	-,054	-,115	-,537	,766[a]

a. Measures of Sampling Adequacy (MSA)

Communalities

	Initial	Extraction
Besar kecilnya Hypermart-jauh dekatnya lokasi	1,000	,744
Besar kecilnya Hypermart-kemudahan akses	1,000	,779
Besar kecilnya Hypermart-strategisnya lokasi	1,000	,717
Sedikit banyaknya komposisi produk -jauh dekatnya lokasi	1,000	,736
Sedikit banyaknya komposisi produk -kemudahan akses	1,000	,795
Sedikit banyaknya komposisi produk -strategisnya lokasi	1,000	,613
Baik buruknya citra layanan -jauh dekatnya lokasi	1,000	,813
Baik buruknya citra layanan -kemudahan akses	1,000	,868
Baik buruknya citra layanan -strategisnya lokasi	1,000	,794

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,020	33,561	33,561	3,020	33,561	33,561	2,473	27,475	27,475
2	2,150	23,888	57,449	2,150	23,888	57,449	2,234	24,826	52,301
3	1,689	18,767	76,216	1,689	18,767	76,216	2,152	23,916	76,216
4	,650	7,218	83,434						
5	,460	5,110	88,544						
6	,324	3,605	92,148						
7	,292	3,242	95,391						
8	,269	2,985	98,375						
9	,146	1,625	100,000						

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component		
	1	2	3
Baik buruknya citra layanan -kemudahan akses	,800	,067	-,473
Baik buruknya citra layanan -strategisnya lokasi	,776	-,072	-,431
Baik buruknya citra layanan -jauh dekatnya lokasi	,724	,058	-,534
Besar kecilnya Hypermart-kemudahan akses	,637	,190	,581
Besar kecilnya Hypermart-jauh dekatnya lokasi	,631	-,146	,569
Besar kecilnya Hypermart-strategisnya lokasi	,621	,131	,560
Sedikit banyaknya komposisi produk -kemudahan akses	,052	,887	,069
Sedikit banyaknya komposisi produk -jauh dekatnya lokasi	-,247	,818	-,080
Sedikit banyaknya komposisi produk -strategisnya lokasi	,007	,779	-,085

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Rotated Component Matrix[a]

	Component		
	1	2	3
Baik buruknya citra layanan -kemudahan akses	,918	,154	,038
Baik buruknya citra layanan -jauh dekatnya lokasi	,899	,058	,036
Baik buruknya citra layanan -strategisnya lokasi	,871	,160	-,101
Besar kecilnya Hypermart-kemudahan akses	,119	,866	,122
Besar kecilnya Hypermart-strategisnya lokasi	,120	,836	,065
Besar kecilnya Hypermart-jauh dekatnya lokasi	,117	,828	-,212
Sedikit banyaknya komposisi produk -kemudahan akses	,012	,154	,878
Sedikit banyaknya komposisi produk -jauh dekatnya lokasi	-,123	-,156	,835
Sedikit banyaknya komposisi produk -strategisnya lokasi	,074	-,001	,780

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 4 iterations.

Component Transformation Matrix

Component	1	2	3
1	,767	,638	-,064
2	,019	,077	,997
3	-,641	,766	-,047

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Lmapiran 5. isian Kuesioner Responden

Resp	Karakteristik						Ukuran Toko				Komposisi				Citra			
	J.Kelamin	Status	Usia	Pekerjaan	Pengeluaran	T.Tinggal	1	2	3	Jml	1	2	3	Jml	1	2	3	Jml
1	2	1	1	1	1	1	4	5	5	14	4	5	4	13	4	5	4	13
2	2	2	1	5	2	3	4	4	5	13	2	3	4	9	5	5	5	15
3	1	1	1	2	3	2	3	4	3	10	4	4	5	13	4	4	5	13
4	1	2	2	4	2	2	4	5	5	14	4	5	4	13	4	5	4	13
5	2	2	2	5	2	1	4	5	5	14	2	2	2	6	3	4	4	11
6	2	1	2	2	2	3	4	5	5	14	2	2	2	6	4	5	5	14
7	1	2	3	2	3	3	4	5	4	13	2	2	2	6	4	5	5	14
8	1	2	2	2	4	3	4	4	5	13	2	4	5	11	4	5	4	13
9	1	1	2	3	2	3	4	5	5	14	4	5	4	13	4	4	4	12
10	1	1	2	2	3	3	4	5	4	13	4	4	4	12	4	5	5	14
11	2	2	2	5	3	1	4	5	4	13	4	5	5	14	4	4	5	13
12	1	2	3	3	2	1	4	5	5	14	4	5	4	13	4	5	5	14
13	1	1	2	3	2	2	4	5	4	13	4	5	4	13	4	5	4	13
14	2	2	3	3	2	1	4	5	5	14	5	5	4	14	4	5	5	14
15	1	2	3	4	2	1	4	5	5	14	4	5	4	13	4	5	4	13
16	1	1	2	3	2	1	5	3	3	11	2	4	4	10	4	4	4	12
17	2	2	3	5	2	3	2	4	4	10	5	5	5	15	5	5	5	15
18	2	2	4	5	4	3	3	2	3	8	4	3	5	12	3	4	3	10
19	1	1	1	1	1	4	2	2	2	6	3	3	4	10	5	5	4	14
20	1	2	3	2	2	3	3	5	5	13	5	5	5	15	5	3	2	10
21	2	1	2	3	2	3	4	4	5	13	4	5	5	14	4	5	4	13
22	1	1	2	2	2	1	2	2	1	5	4	4	3	11	4	4	4	12
23	2	1	1	2	1	1	2	3	1	6	3	4	5	12	4	4	3	11
24	2	1	2	2	2	1	4	5	4	13	5	4	4	13	3	4	4	11
25	1	2	2	2	3	3	4	4	3	11	3	3	3	9	4	3	4	11
26	1	2	2	3	2	3	4	4	4	12	3	4	4	11	4	4	4	12
27	1	1	2	3	2	5	4	4	4	12	3	3	4	10	4	4	4	12
28	1	2	3	3	2	4	2	4	2	8	5	5	4	14	5	5	5	15
29	2	1	2	3	3	3	2	4	2	8	5	5	2	12	1	1	1	3
30	2	2	4	5	2	3	4	4	4	12	4	4	4	12	4	4	4	12
31	2	2	4	5	2	3	2	2	2	6	4	4	4	12	4	4	4	12

32	2	2	3	3	2	1	4	4	5	13	2	3	3	8	3	2	2	7
33	2	2	3	5	2	1	2	4	4	10	5	5	3	13	5	5	5	15
34	1	2	4	3	2	2	2	3	2	7	5	3	2	10	1	3	2	6
35	2	2	4	2	3	1	4	4	3	11	2	3	4	9	4	4	4	12
36	1	1	1	1	1	1	4	4	1	9	1	4	2	7	5	5	5	15
37	1	1	2	2	2	1	2	3	3	8	4	4	4	12	4	4	4	12
38	2	2	4	5	2	3	4	3	4	11	2	2	2	6	4	4	5	13
39	2	1	2	2	2	3	4	3	1	8	4	4	4	12	4	4	3	11
40	2	1	2	2	3	4	2	2	2	6	3	4	5	12	3	3	3	9
41	2	2	4	3	2	4	4	4	2	10	5	5	5	15	4	4	2	10
42	1	2	4	2	4	2	2	4	4	10	4	2	4	10	5	3	4	12
43	2	1	1	3	2	2	3	3	3	9	3	3	3	9	5	5	5	15
44	2	1	2	3	2	1	2	3	3	8	4	4	5	13	4	4	3	11
45	2	2	4	5	3	3	3	4	4	11	5	5	5	15	4	5	5	14
46	2	2	3	5	2	1	2	3	3	8	4	4	5	13	5	5	5	15
47	1	1	1	1	1	1	4	4	3	11	2	3	2	7	3	3	4	10
48	1	1	1	1	2	1	2	2	3	7	4	4	5	13	1	1	1	3
49	1	2	3	3	2	2	2	2	4	8	5	5	5	15	5	5	5	15
50	1	2	3	2	4	1	3	4	3	10	4	4	3	11	5	5	4	14
51	1	1	1	3	2	1	3	3	2	8	4	5	5	14	4	4	4	12
52	1	1	1	3	2	2	3	3	4	10	4	4	3	11	2	3	3	8
53	1	2	3	4	3	3	5	5	4	14	5	5	5	15	3	3	4	10
54	1	2	4	3	2	3	4	3	4	11	2	3	2	7	3	4	5	12
55	1	1	2	3	2	4	3	4	4	11	3	3	4	10	3	3	4	10
56	1	2	3	2	4	4	3	3	2	8	3	4	4	11	5	5	5	15
57	1	2	4	2	4	5	3	3	3	9	2	3	3	8	4	4	3	11
58	2	1	2	2	2	4	3	4	4	11	3	4	3	10	3	3	4	10
59	2	2	2	3	3	4	4	4	4	12	3	4	3	10	4	4	3	11
60	2	2	2	3	3	3	2	3	2	7	2	2	3	7	4	4	4	12
61	1	1	1	1	2	2	3	4	3	10	5	5	5	15	5	5	5	15
62	1	1	1	2	2	1	2	2	2	6	4	5	4	13	2	2	2	6
63	2	2	3	2	3	1	2	2	2	6	4	4	5	13	2	2	2	6
64	1	2	2	3	2	1	3	3	4	10	3	4	3	10	3	3	4	10
65	2	1	1	3	2	2	3	3	4	10	3	3	4	10	4	3	3	10
66	1	1	1	3	2	1	3	3	3	9	3	3	4	10	3	3	3	9
67	2	2	2	5	2	1	2	3	3	8	3	3	4	10	3	3	4	10

68	2	2	3	5	3	3	3	3	3	9	3	3	3	9	3	3	3	9
69	2	1	2	3	2	3	1	4	1	6	4	4	5	13	2	2	3	7
70	1	1	1	1	1	3	4	5	4	13	4	4	4	12	5	5	4	14
71	1	2	3	2	4	4	4	4	3	11	2	4	4	10	2	2	4	8
72	1	2	3	3	2	4	3	3	4	10	2	3	2	7	4	4	3	11
73	2	1	1	2	2	3	1	2	2	5	4	3	3	10	4	4	4	12
74	2	1	2	3	2	3	3	3	1	7	4	4	3	11	3	4	4	11
75	2	2	2	2	3	1	4	5	5	14	2	2	2	6	4	5	4	13
76	2	2	3	3	3	1	4	4	5	13	2	2	2	6	5	5	5	15
77	2	1	2	2	2	3	3	4	3	10	4	4	5	13	4	4	5	13
78	1	2	3	3	2	1	4	5	5	14	4	5	4	13	4	5	4	13
79	1	2	3	3	2	1	4	5	5	14	4	4	5	13	3	4	4	11
80	1	2	3	2	3	1	4	5	5	14	4	5	4	13	4	5	4	13
81	1	2	3	2	2	1	5	3	3	11	2	4	4	10	4	4	4	12
82	2	1	2	3	2	3	2	4	4	10	5	5	5	15	5	5	5	15
83	2	1	1	1	1	1	3	2	3	8	4	3	5	12	3	4	3	10
84	1	1	1	4	3	3	2	2	2	6	3	3	4	10	5	5	4	14
85	1	2	3	3	2	3	3	5	5	13	5	5	5	15	5	3	2	10
86	2	2	3	5	2	4	4	4	5	13	4	5	5	14	4	5	4	13
87	1	1	2	3	2	3	2	2	1	5	4	4	3	11	4	4	4	12
88	2	1	1	1	2	3	2	3	1	6	5	2	1	8	4	4	3	11
89	1	2	3	2	3	2	4	4	3	11	3	3	3	9	4	3	4	11
90	1	2	2	3	4	1	4	4	4	12	3	4	4	11	4	4	4	12
91	1	2	2	2	2	1	4	4	4	12	3	3	4	10	4	4	4	12
92	2	1	1	2	2	1	2	4	2	8	5	5	4	14	1	1	1	3
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94	2	2	3	5	2	1	2	2	2	6	4	4	4	12	4	4	4	12
95	2	2	3	5	2	2	4	4	5	13	2	3	3	8	3	2	2	7
96	2	2	4	2	3	2	2	4	4	10	1	4	2	7	5	5	5	15
97	1	1	2	3	2	1	2	3	2	7	5	3	2	10	1	3	2	6
98	2	1	1	3	3	1	4	4	3	11	2	3	4	9	4	4	4	12
99	1	2	4	4	3	3	4	4	1	9	2	2	3	7	5	5	5	15
100	1	2	4	3	2	3	2	3	3	8	4	4	4	12	4	4	4	12
						mean	3.17	3.67	3.36		3.5	3.81	3.76		3.78	3.95	3.83	
						SD	0.954	0.965	1.243		1.078	0.95	1.026		1.001	1.019	1.006	

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Multi-outlet retail site location assessment[1]

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Abstract

One of the most important decisions a retailer can make is where to locate a retail outlet. Because convenience is so important to today's consumers, a retail store can prosper or fail solely based on its location. Recently, a changing retail environment is augmenting the location importance as retail economic groups develop multi-outlet chains of small stores. The methods used in the development and calibration of location models for commercial spaces and sales forecast are multiple, varying from simple analogy forecast models to very complex spatial interactions models, which may incorporate dependence models in a gravitational or logit structure and many exploratory variables. More recent developments incorporating meta-heuristics such as genetic algorithms for the global problem of the multi-outlet chain configuration, or the use of Voronoi diagrams in store trade area delimitation, are also presented. Finally, the Geographical Information Systems' role on the decision support process is equally explored.

Keywords: Marketing; forecasting: applications; retailing; turnover assessment; Geographical Information Systems; Voronoi diagrams.

Introduction

In spite of the heterogeneity observed in different European countries, generically the retail sector is going through a restructuring phase. Birkin, Clarke and Clarke (2002) mention such factors as increasing consumer mobility, increasing electronic commerce, changing household size,

[1] This paper is a tribute to Professor Isabel Hall Themido, who has recently deceased, and who was responsible for the conception and main body of the work.

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concentration of market power, home market saturation, and changes in planning legislation to justify the new trends in retailing. In the food retail, in particular, after an unprecedented period of growth of hypermarkets since the late 1970s, both in number and market share, it is now clear that hypermarket activity has slowed down significantly in favor of the small or medium supermarkets that nowadays present a larger dynamism. This is true in countries such as Germany, France, United Kingdom, Portugal, and Spain.

This change in the consumer's behavior and the fact that consumers are more demanding force the retail groups to invest strongly at stores of smaller dimension, betting on a proximity and quality of goods and services strategy. This investment has a longer-run return as well as smaller economies of scale, which forces careful decision-making. Crucial aspects for the success of smaller retail shops as the location, dimension, services offered, and targeting to specific market segments are receiving special attention. In this context, the development of decision support systems based on quantitative models assumes an increased relevance.

Figure 1 represents a possible schema for different levels of retail-network location decisions. We consider a phased decision methodology, although the interaction among the different phases is possible, especially between the services offered and store location (levels 2 and 3). Studies based on enquiries, as the one presented in Birrell and Worrall (1995), indicate that the decision-maker separates decisions about choosing geographical regions and choosing store locations within the region.

In a first phase, based on expansion strategic policy for the network, a zone or region where new stores will be installed, the number of units to be built, along with implementation timings are selected. Lilien and Kotler (1983) named this group of interlinked problems the macro problem, in contrast to site location, which is the micro problem, analysed in this paper.

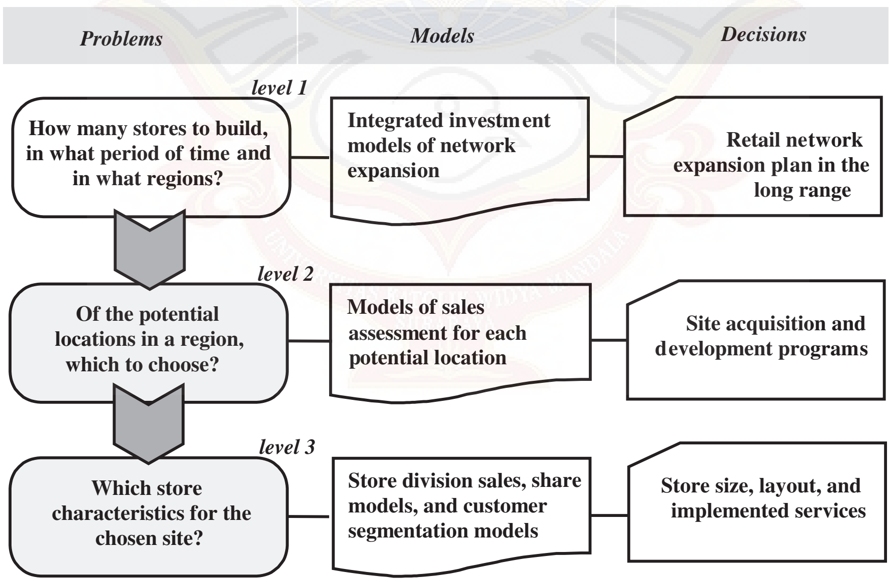

Fig. 1. Decision levels involved in the expansion strategy of a multi-outlet retail network. (Adapted from Lilien and Kotler, 1983).

After the selection of some alternative locations is made, usually with the help of real estate agencies, it is intended, in a second phase, to accomplish the final store-site choice. For this decision level, the number of commercial plus academically published models suggests that researchers (in addition to managers) feel a need for rational and formal use of information.

The third decision level, concerning store and services design, is the level most linked to the concept of service quality and customer satisfaction as mentioned in Sulek, Lind and Maruchek (1995). As observed, the physical design of the service facility has an important role to play. This paper will focus essentially on the models used in decision support systems (DSS) regarding store location (level 2). However, some of them can be extended for application in the store characteristics and services definition (level 3).

Retailers have always understood location as paramount, but understanding all aspects of store performance, site potential in addition to consumer behavior demands a great amount of information, including geographical, demographic, socio-economic, and competition data. Figure 2 suggests a possible classification of assessment location explanatory variables. In opposition to trade area evaluation (demand and competing offer), the site and store variables intend to evaluate internal factors or the new store offer. Store size is traditionally singled out as the most important outlet characteristics, as an independent branch of the schema outlines.

Classical procedures

Development of accurate sales forecast is central to successful retail-site selection (Kotler, 1984). However, empirical methods of retail sales forecasting suffered from an excessive subjectivity of analysis, as well as an inability to consider simultaneously the impacts of multiple variables. Progressively, statistical sales forecasting methods contributed to define the relationships between

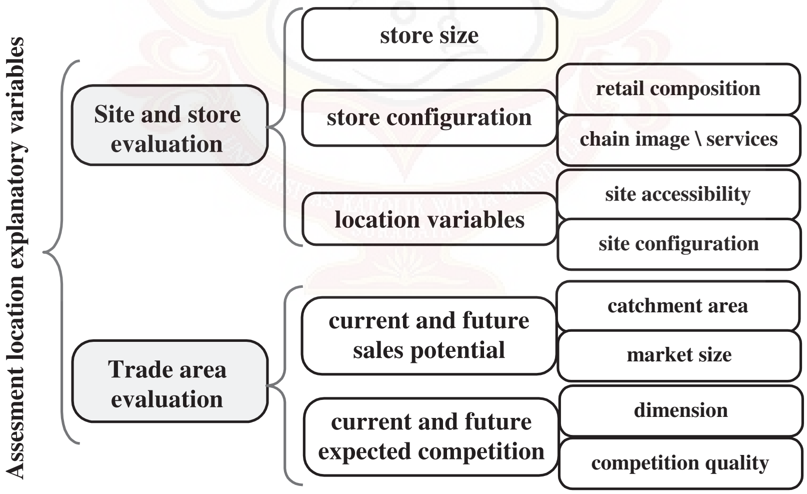

Fig. 2. Classification of assessment location explanatory variables. (Adapted from Themido, Quintino and Leitão, 1998).

store sales and influential variables, such as site, demographics along with competitive characteristics. Pastor (1994) also emphasizes the importance of new techniques focusing both on finding optimal sites for new outlets and forecasting sales, based on objective criteria.

In the mid-1980s, a medium-sized UK supermarket chain, Tesco plc, decisively invested in a remarkably successful project aimed at forecasting store turnover with only 10% mean error. The need of such an expensive and long study is justified in the words of Attewell (1991) by the fundamental need to make better site-acquisition decisions, thus reducing the risk associated with multi-million-pound investments. They began with simple regression models, evolving later to gravitational models. Tesco plc planned the construction of 12 new stores a year, adding to the existing 360, obtaining excellent results with the methods developed by consultants, Penny and Broom (1988), later on continuing in-house development. The value of store location analysis is now well established at Tesco, and is considered a commercial advantage (see Cummings, 1999). Today Tesco has 678 stores and is the largest retailer in the United Kingdom, with 15.6% of the food market.

This section focuses on classical procedures, such techniques and models as analogue techniques and gravitational models which are heavily used and studied nowadays in spite of been known for many years. The last three sections concentrate on newer, promising approaches and trends on the problem of locating retail stores, on trade area delimitation and on using GIS for location analysis.

Analogue-based procedures

The simplest site-selection technique involves rules of thumb used by location analysts that apply a combination of experience and empirical observation, along with trial and error to isolate the key factors which appear to affect directly the performance of a store location. One example is the checklist method referred in Lilien and Kotler (1983), which includes eight major site factors, each one divided into several attributes. A manager checks each factor separately for the proposed location and analogue stores used for constructing a profile of the strengths and weaknesses of the sites. Those profiles are then compared, and a rating is produced based on empirical rules and weights. Such methods are relatively inexpensive and may offer rapid solutions for a location decision (Sulek, Lind and Maruchek, 1995). However, these simple rule-based methods may be over-simplistic and subjective.

The analogue-based forecast models are a natural outcome of the former attempt to overcome their lack of objectivity. Developed by Applebaum (1966) since the 1930s, analogue methods, in their simpler form, do not require many data, are reasonably objective, and allow the inclusion of the analyst's business experience and intuition. These models are still used by companies when the chain's number of stores does not justify the development of more advanced models.

The methodology starts by classifying several analogue commercial spaces according to a group of store attributes as empirical benchmarks. Each store in the analogue group is evaluated, and the location-related factors of the new site are measured against a pre-defined scale. Using weights or other simple techniques, a store-sorting list is then produced which rates the new store relatively to the remaining ones. A forecast interval for the sales of the new store is thus defined.

This interval is as narrow as the annual sales difference between the stores rated immediately before and after the new store.

This methodology, just as other methods of site ranking, can equally identify business opportunities areas. A large Portuguese retail group uses this method. The procedure starts by identifying key variables that characterize the trade area. Those variables are then used in the identification of analogue areas. By considering the number of stores or the total floor space already installed in comparison with the sales potential of the analogue areas it is possible to conclude whether or not it has potential for the installation of new stores. This method is put into practice with the aid of GIS packages, in addition to extensive databases including stores of several chains controlled by the same and competing retail groups.

Recent projects explore a combination of intuitive insight with normative approaches to develop analogue-based decision support systems. A recent example is the work presented by Clarke, Mackaness, Ball and Horita (2001). These authors describe how the analogies identified by a qualitative system can be visualized effectively for use in location analysis. They use cognitive mapping and other visualization techniques for exploratory data analysis and decision support.

Analogue-based forecast models have been appearing, in recent years, associated with statistical techniques. Examples are the analogues based on regression models referred by Simkin (1989) in his survey conducted among UK multiple retailers, which at the time was the primary location procedure used, and discriminant analysis. Another example is cluster analysis in analogue store group formation and market segmentation (Cardoso and Mendes, 2002; Schaffer and Green, 1998).

Gravitational models

Gravitational models are derived from the laws of Newtonian physics, based on the balance between the store attractivity and the distance to the potential customers. In the initial work of Reilly (1931), the law of retail gravitation related the share of customers that an outlet attracts as being inversely proportional to distance they must travel and directly related to the store dimension. A similar formulation was pioneered by Huff (1963) to calculate a probability that a customer patronizes a facility.

Gravitational model procedures start with the definition of the trade area of a store location. This area is then divided in smaller zones of homogeneous demographic environments in addition to competitive characteristics, respecting geographical obstacles like rivers, motorway lines, railways, etc. Each zone is than analysed for the calculation of potential sales originating in that zone (E_i). The distribution of this potential is made by using equation (1) for several sale points (which include the future store as well as the competition) according to a distance function (t_{ij}^b) where the parameter b, actually determined by regression for analogue stores, reflects the sensitivity of costumers to distance. In that equation, A_j symbolizes attractivity of store j, S_{ij} stands for the store j turnover fraction originating in zone i. Total sales for store j are estimated by summing S_{ij} for all zones in the trade area.

$$S_{ij} = \frac{E_i \cdot A_j / t_{ij}^b}{\sum_j A_j / t_{ij}^b} \tag{1}$$

This model evolved from store dimension to include a variety of other factors in the attraction concept as competition or demographic variables, which could extend to the multiple-retailer context (Kotler, 1984; Rogers, 1992). An example is the work presented by Stanley and Sewall (1976) where multiple site or store variables characterizing the different stores of a network are aggregated in an attractivity measure, using multi-dimensional scaling techniques. Fernandes and Themido (1997) present another example of a recent application of these models to a problem of turnover forecast for different locations of service stations. In their work, they conclude that in the particular case of service station, retail trade areas are especially difficult to define and recommend a combination of gravitational and simple dependence models.

These procedures are used to evaluate alternative total network configurations in a market. It has also the advantage of explicitly incorporating distance among sales points as well as considering items as population and competition, which, in highly competitive markets can be decisive (see Kaufmann and Rangan, 1990). They can also provide estimates of sales impacts on the construction layout modifications or amplification of sale points on competition as cannibalism in sister stores. Therefore, they seem uniquely suited for locational strategies simulation in the long run (see examples in Rogers, 1992).

However, this type of model is difficult to calibrate, as it demands a great volume of data, so users tend to apply it in the evaluation of one new site at a time (Boufounou, 1995) reducing the model's practical utility. Heald (1972) stresses often the distance function related with the attractiveness, and mentions that it could present difficulties in correctly estimating the parameters. The same author claims that the gravity models have difficulties in leading with competition other than spatial, such as parking space, service, and quality of products. They also have little sensitivity to demographic variations or market segmentation, i.e. they are *segmentation blind*. For this reason, they should not be used for specialized retailing.

In European applications of gravitational models, there are additional obstacles as it becomes obvious the difficulty in considering the impact of differential mobility levels (Rogers, 1992) and in the correct estimate of trade areas potentials. According to Kotler (1984), this comes from Europe's higher percentage of public transportation and customers' uncertain behavior. In the United States, these obstacles are not as effective as forms of more homogeneous as well as geometric urbanization, intensive use of individual transportation, existence of higher volumes of statistical data on the consumers and the tradition of strong company planning departments, decisively contributed to the USA's leading role in gravitational models application.

Recently, some authors as Birkin, Clarke and Clarke (2002) and Dugmore (1997) claim that gravitational models and more generally spatial interactions models are receiving more interest as more data and GIS technologies are becoming available.

Analogue-based regression models

This is one of the most commonly applied store-turnover forecasting models (Hernández and Bennison, 2000; Morphet, 1991). It was first applied to retail location analysis in the 1960s. It is particularly appropriate for retailers with highly segmented market appeals, for example, clothing retailers, restaurants, bookshops, and jewelers, but is widely used and misused in all areas of retail (Kotler, 1984).

The variables are measured for existing stores, which are reasonably analogous to new locations in study. Those data are then used to calibrate a linear statistical equation. It is important to note that the equation includes just those variables, termed independent or predictor variables, which are found to be significantly correlated with store turnover. Their uses simply involve entering the measurements for a new site on the relevant predictor variables and compute the required estimate of store turnover.

An example of a dependence model with some complexity is the *Store Location Assessment Model* (SLAM) described by Simkin (1989), which uses addictive or multiplicative expressions and many variables. In these models, demographic as well as competitive variables can be defined in relation to one or more zones of the new store retail trade area, and different models can evaluate each zone.

Themido, Quintino and Leitão (1998) present an example for the Portuguese retail gasoline market. Those authors obtained a total of seven linear and multiplicative regression models: one for a general case, named basic model, and six for the same number of service station segments. The estimates produced were more accurate than those made by previous models and are currently being used to support investment decisions of the largest Portuguese company. Themido, Quintino and Leitão also introduced the concept of *anchor variables* as a model-selection criterion. For identical quality of fit, models with better stability of the parameters of the anchor variables were favored in order to obtain marketing consistency and interpretability.

Regression techniques are also used in attraction models parameter calibration that may be applied to multi-outlet store assessment, as the work presented by Achabal, Gorr and Mahajan (1982) proves. In this work, the development of a MULTIple store LOCation (MULTILOC) model extends the multivariate competitive interactive (MCI) model to the multi-store location problem, utilizing a random search procedure combined with an interchange heuristic to identify optimal or near-optimal sets of locations.

Most of the methods devoted to model the competition in the retail system and measure the impact effects of the transformations that are taking place are multinomial logit (MNL) and multiplicative competitive interaction (MCI) models, derived form spatial interaction and discrete choice theories (see for instance Drezner, 1995; Kaufmann, Donthu and Brooks, 2000; Wong and Yang, 1999). Despite their solid theoretical structure, these models present some behavioral and structural anomalies, like the dependence from irrelevant alternatives and non-regularity properties (see Mendes and Themido, 1998, for a recent review). To overcome these anomalies, techniques like nested logit models, competition destination models, and the paired combinatorial logit model, have been proposed (Fotheringham and O'Kelly, 1989; Koppelman and Wen, 2000).

One recent example is the work by De Giovanni, Sanlorenzo and Tradei (2003) where a modeling framework is presented to determine an interaction matrix and a singly constrained logit model for the retail system impact analysis. For an application on the Provincia di Milano in Italy, the authors found that the opening of a modern store has less impact, in percentage, among existing modern stores than traditional ones, but a modern store located far away is more impacted than a corresponding traditional one. In the opinion of De Giovanni, Sanlorenzo and Tradei (2003) this is explained by the fact that modern stores competition is much more spread out, generating overlapping trade areas.

Both Simkin (1989) and Rogers (1992) defend the use of a large number of possible explanatory variables in order to avoid the exclusion of some significant variable during the first stages of the analysis. They also defend the extensive use of automatic variable selection techniques. Other authors such as Newsome and Zietz (1992) consider the necessity of segmentation, especially when the dependent variable variances are significantly different between the segments.

The main obstacle to the use of this method is the high number of necessary observations, as much as more explanatory variables are included in the model and more segments are to be considered. The secret that surrounds competition information makes it difficult to obtain the necessary number of observations. This explains why mainly companies with a high number of own sale points have used these models. Regression techniques do not consider outlets as an entire network, but rather evaluate sites in isolation. They treat all customers within the trade area the same way, regardless of their actual distance from the site, and they evaluate specific sites, but do not search for optimal ones (Boufounou, 1995). The difficulties in evaluating some factors in numerical scales is another weakness in applying regression or gravity models, which can be overcome by applying discriminant procedures.

Discriminant analysis

Applications of multiple discriminant analysis for turnover modeling and site location usually support medium to short-term planning decisions, in particular evaluation of specific sites, rather than the strategic planning decisions addressed by other more general models (Sands and Moore, 1981). Typically, the technique is employed as a site-screening tool or as a decision system for relatively low-investment risk situations as it is possible to advise quite simple operating rules (Kotler, 1984).

Unlike regression, this technique analyses existing store performance in order to identify those variables that best explain the differences between pre-selected groups of stores. Once developed, new sites are allocated to the appropriate store turnover group, and the sales range for the group which is used as prevision. This technique is highly sensitive to poor data collection or an inadequate research design.

Morgan and Sonquist (1963) developed another example specifically drawn for problems with a high number of variables in multiple scales. This method, automatic iteration detecting (AID), is a non-parametric classification technique, based on variance analysis, and it segments the observations in different groups, for which regression models can be developed (Heald, 1972).

Recent algorithms for classification or discriminant trees include chi-square automatic interaction detection (CHAID), classification and regression trees (C&RT) and QUEST (quick, unbiased, efficient, statistical tree). Another interesting project in this field is the SODAS (statistical official data analysis software) for analysis of data objects. This software is included in a EUROSTAT project that congregates 17 European scientific groups, one of which developed the strata decision tree (SDT).

The method is a generalized recursive tree-building method that includes strata structures in the tree-building algorithm. In each step, it combines the maximization of an information content measure for the criterion variable in a new binary partition of the population and selection of decisional nodes. Each decisional tree node is composed of a set of strata and a rule for individuals in these strata, which will jointly explain the criterion variable. The algorithm is developed for classical data descriptions as well as for probabilistic data description for individuals (Llatas and García-Santesmases, 2000).

The main disadvantage of these methods is its complexity in terms of necessary calculations in addition to the high data exigency so that the results are significant. Simmons (1987) suggests a minimum of 1000 observations. However, it has influenced many of the subsequent applications of multiple data analysis in the area of turnover assessment. In addition, it is an invaluable tool in the analysis of survey data, indispensable in store-location studies.

Multi-criteria decision analysis procedures

Multi-criteria analysis procedures are frequently used in complex decision and evaluation problems, such as store location. In these procedures, emphasis is on the several objectives the decision-makers can have in mind when choosing a site.

The analogue forecast models could be seen as an example of these methods. Thus, to rank a group of stores and\or potential locations according to location-related factors, multi-objective analysis techniques can be used. One example that explicitly uses decision theory techniques and trade-offs is mentioned in Birrell and Worrall (1995). Their method consists in using in-depth interviews, based on semantic differential scaling questionnaires, to profile the 'ideal' location favored by a decision-maker. This profile is then matched with similar profiles of locations held on a computer database by a real estate agency. The decision-maker is then required to indicate the level of importance he attaches to various location choice criteria which are used in the visual comparison of the best-fit locations. The matching process includes the need for the decision-maker to compromise to a certain extent over his requirements until a satisfying solution is achieved. Similarly, for analogue-based models and discriminant analysis techniques, these methods only forecast store turnover inside relatively wide intervals.

The traditional location multi-criteria decision theory models are used mainly in the context of sporadic locations not involved in a multi-outlet chain. An example of this can be found in Martel and Belaïd (1992), where 12 different criteria are identified for the classification of four possible locations of an airport in a cold area. Other problems locate facilities in a competitive environment. As Karkazis (1989) explains, this consists in locating new shops of a second company, given that a first company has already established a number of shops in a region represented by a network. He generalizes this problem by considering different types of shops, including the determination of the shops number in view of a given budget constraint, and considering other criteria besides distance. These models make difficult the calculation of turnover forecasts, and use aggregation functions not very easily understandable for the decision-maker. In opposition, the sales work equally as an aggregation function but are used and recognized by the managers as well as decision-makers.

In the rich literature existing on competitive location in the plane or location-allocation theory, the more common approaches use mathematical programming formulation, vector optimization, penalty function approaches, convex combination, as well as specific algorithm design (Buhl, 1988; Drezner, Drezner and Salhi, 2002). In spite of objective functions always include some distance or cost objective frequently based in spatial interaction models, they are not adequate for forecasting sales, and are not reviewed here. For a revision on such literature, see for instance Hamacher and Nickel (1996) or Drezner (1995).

Genetic algorithms in the optimal retail location problem

Genetic algorithms were invented by Holland (1975) to mimic some of the processes of natural evolution and selection. As explained in Hurley, Moutinho and Stephens (1995) the first step is to represent a feasible solution to the problem by a string of genes, which can take some value from a specified finite range or alphabet. This string of genes, which represents a solution, is known as a chromosome. An initial population of feasible chromosomes is constructed at random, and then the fitness of each chromosome in the population is measured using a fitness function. The better chromosomes are then crossed using genetic operators to produce offspring for the next generation, which inherit the best characteristics of both parents. After many generations, the result is hopefully a population, which is substantially fitter than the original one. These algorithms can be used in many difficult problems, but they do not assure that optimality is reached and so are known as meta-heuristics.

Genetic algorithms can be combined with algorithms of neural nets or knowledge-based systems leading to more complex evolutionary models. A review of evolutionary algorithm for marketing optimization problems is presented in Hurley, Moutinho and Stephens (1995). These authors mention the application of genetic algorithms to the optimal retail location problem. A new store is evaluated considering the competition from all other stores, from the same or competing chains, already existing. This problem, presented in Curry, Moutinho and Davies (1993), consists in finding the optimal network of locations within a group of existing stores plus other potential locations for new stores. Using this overall view of the retail network in an area, expansion becomes a planned progression rather than a sequence of arbitrary decisions. The algorithms also allow examination of alternative scenarios for actions of the competition and of the chain under analysis.

This meta-heuristic algorithms can be easily used to solve several variants of the problem: choosing new locations in order to improve the global performance of the retail chain; choosing new locations with the possibility of closing existing ones; or choosing a group between existing locations to implement a new service or product.

In genetic algorithms, the fitness function is of primordial importance and usually corresponds to the largest modeling effort, as the quality of the results is strongly dependent on fitness function accuracy. In store location, this function could be a sales forecast model that should apply for new as well as existing locations. Models based on gravitational methods, as the ones presented in Achabal, Gorr and Mahajan (1982) are a possibility. The fitness function must consider the effect of competing stores since this effect is not otherwise considered in the genetic algorithm. The same function can be based in more elaborated models as the one presented by Kaufmann, Donthu and Brooks (2000) which use other spatial interaction models and include opening delays.

There are other knowledge-based meta-heuristics as expert systems and neural networks that have been used for store performance forecasting (Coates, Doherty, French and Kirkup, 1995) and spatial analysis (Murnion, 1996). Other promising algorithms as hybrid heuristics could also be used (Cavique, Rego and Themido, 2002), but applications are scarce, maybe because they involve very high technical expertise and data requirements, and so, high costs.

Voronoi diagrams in trade area modelling

One of the main difficulties encountered in the application of gravitational or other dependence models is the definition of a store retail trade area, which is essential for turnover evaluation (see Fig. 2). A common geometrical diagram, called the Voronoi diagram (Voronoi, 1908), allows the combination of location information and other store attributes, with consumer behavior, to generate influence areas (Gonçalves and Mendes, 2002).

Voronoi diagrams are often attributed to Thiessen Voronoi or Dirichlet (hence the name 'Dirichlet tessellations', also used). By now, there is an impressive amount of literature concerning Voronoi diagrams and their applications in all kinds of research areas. (For an extensive commented review, please see Berg, van Kreveld, Overmars and Schwarzkopf, 2000).

The application of these diagrams to store location problems is extensively discussed in Boots and South (1997) but earlier references can be found. The Voronoi polygons can be used for descriptive or prospective purposes, allowing a graphic representation of the problem helping to identify new locations as well as to visualize the impact of alterations in existing stores. Another advantage over the multinomeal logit MNL model is that Voronoi polygons do not require complex statistical calibration procedures. In addition, they can be used without data on store preference by individual customers.

In its simpler form, the Voronoi diagram is easily defined given a finite set of two or more distinct *polygon generation points* ($P = \{p_1, p_2, \ldots, p_n\}$ with $2 \leqslant n < \infty$). Associating all locations in that space with the nearest member of the point set, a tessellation of the plane into a set of regions is obtained. This simple tessellation is called the ordinary Voronoi diagram (OVD), and the regions constituting the diagram, ordinary Voronoi polygons (Okabe and Suzuki, 1997). Formally,

$$V(p_j) = \{p : \|p - p_j\| \leqslant \|p - p_l\| \text{ for } j \neq l,\ l = \{1, 2, \ldots, n\}\} \tag{2}$$

where $||p - p_i||$ is a Euclidian distance between p and facility p_i, the resulting $V = \{V(p_1), \ldots, V(p_n)\}$ is a tessellation of the working space, i.e. an OVD. Clearly, $V(p_i)$ contains all locations, which are closer to facility p_i than to any other facility.

This very simple model considers that two stores are equally attractive for the consumer if they are at the same Euclidian distance. It has the disadvantage of considering a homogeneous space without geographical barriers. Nevertheless, it is a very easily applied model that can be valid in densely populated zones, without geographical barriers in addition to relatively homogeneous demographic and psychographics factors. No less important is the existence of readily available algorithms that run in $O(n \log n)$ time in the most well-known GIS packages (Berg, van Kreveld, Overmars and Schwarzkopf, 2000).

In multiplicatively weighted Voronoi diagrams (MWVD), the model assumes that customers choose the store considering a trade-off between proximity and store attractiveness. The

MWOVD polygon is given by:

$$V_w(p_j) = \{p : (1/w_j)\|p - p_j\| \leqslant (1/w_l)\|p - p_l\| \text{ for } j \neq l,\ l = \{1, 2, \dots, n\}\} \tag{3}$$

where $w_i > 0$ is a measure of the attractiveness of the store i, i.e. a function of its variables and attributes.

Other trade area models, like those based on the Reilly gravitational law, assume that a customer's facilities evaluation depends on both facility location and attractiveness. This evaluation is expressed in terms of the utility U_{ij} of facility j for customer i, with the general form:

$$U_{ij} = A_j / t_{ij}^b \, (b \geqslant 0) \tag{4}$$

where A_j is a measure of the attractiveness of facility j and t_{ij} is a function of the distance (or time) between customer i and facility j.[2] Comparing equations (4) and (3) one may notice that if customer i is located at p and $b = 1$ then U_{ij} is the reversal of $(1/w_j)||p - p_j||$. Thus, the MWVD for facility p_j is equivalent to the trade area, demarcated by assigning to p_j all customers for which that facility maximizes this utility function.

These models can be further extended considering those customers frequent k near-by stores, obtaining MWVD order-k diagrams defining areas with non-empty intersections. This is much closer to reality as customers these days often patronize simultaneously local supermarkets as well as superstores with different frequencies and for different shopping baskets. For the MWVD polygon of order-k, consider $Q^{(k)}$ the group of all the possible subsets of k stores of among the n existing ($Q^{(k)} = \{P_1^{(k)}, \dots, P_i^{(k)}, \dots, P_l^{(k)}\}$ and $l = {}_nC_k$). Consider also any of those groups $P_i^{(k)} = \{p_{i1}, p_{i2}, \dots p_{ik}\}$ so the MWOVD polygon of order-k will be given by:

$$V_w(p_i(k)) = \{p : \max_{Ph}[d(p - p_h)/p_h \in P_i(k)] \leqslant \min_{Pi}[d(p - p_j)/p_j \in P \backslash P_i(k)]\} \tag{5}$$

where $d(p - p_i)$ corresponds to the weighted distance between a point of the polygon p and the store p_i, i.e. $(1/w_i)||p - p_i||$. In spite of the complexity of the resulting diagrams (with many small areas) it is possible to find algorithms for solving order-k Voronoi diagrams in $O(n \log^3 n + k(n-k))$ time (Berg et al., 2000).

The polygons define areas that can be represented in diagrams as the one presented in Fig. 3. Given the definition of retail trade areas, by these polygons, it is possible to obtain forecasts of sales considering the distribution of the population in the polygon as well as the mean expense per customer in each store. For such, it is necessary to consider the following assumptions (Okabe and Suzuki, 1997):

- n facilities of the same type are located in a finite, planar region;
- customers patronize one or more of the facilities;
- customers limit their purchase to the k facilities with the higher utilities;
- an individual facility, j, is assigned a weight, $w_j (>0)$, on the basis of its attractiveness to customers in terms of attributes like price, size, parking, etc.

[2] Note that generalizing these utility functions for all sub-areas of a study zone and multiplying by the sales potential of the considered area we can obtain equation (1) for gravitational model sales forecast.

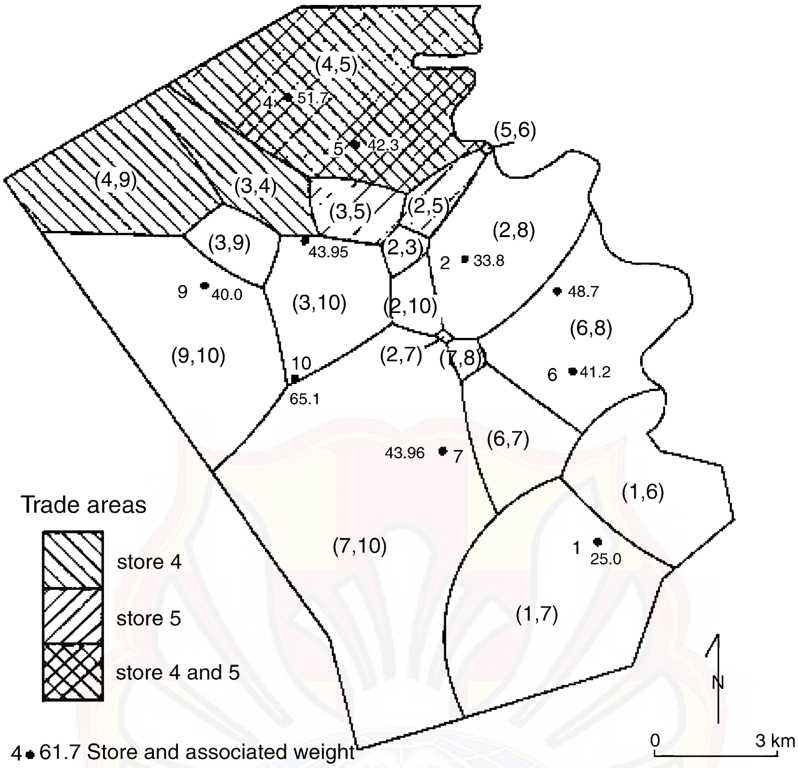

Fig. 3. O2MWVD polygons for a chain of supermarkets. (Reproduced with permission from Boots and South, 1997).

- the utility U_{ij}, of facility j for customer i is an inverse function of the distance traveled by i to reach j, and a direct function of the attractiveness of j (i.e. such as in gravitational models the customer is more likely to select the nearby facility with the highest utility);
- the customer is indifferent to the k facilities so sales will be equally distributed among all the k stores frequented by the consumers inside the polygon, or the customer displays a preference for the highest utility and customers spread their purchases proportionally to the relative utility of the stores.

Okunuki and Okabe (2002) also apply Voronoi tessellations to networks, combining in the resulting trade area the accessibility of road trajectories and the competition of nearby retail stores. Another example of a new promising Voronoi diagram is the centroidal Voronoi tessellation. Du, Faber and Gunzburger (1999) define this tessellation as a Voronoi tessellation of a given set such that the polygon generating points are centroids (centres of mass) of the corresponding Voronoi regions. Therefore, this model can produce simultaneously, locations for new shops as well as their corresponding trade areas, as in location-allocation models. Discrete centroidal Voronoi tessellations are often related to optimal k-means clusters if we use a variance-based criterion.

The use of GIS in store location

In a complex decision process, involving a great variety and volume of information, in addition to an important subjective component, visualization methods are extremely useful. Thus, geographical information systems (GIS), based on a crossing of digitalized cartography in addition to relational databases, will be certainly indispensable for future developments in store location decision support systems.

GIS systems are already an important tool in the decision-making process of retail chains (Hernández and Bennison, 2000). However, there is still a weak integration of these packages with models and decision support methods that provide better-worked information and, in consequence, accomplish more complete analyses. It is possible to couple spreadsheets with GIS applications, taking advantage of the great modeling power of the former as well as the visualization capabilities of the later. These associations between applications are known as loosely coupled, in contrast with solutions that involve the programming of decision support functionalities into the GIS packages or programming GIS functionalities into decision support applications (strongly coupled according to the terminology used in Klosterman and Xie, 1997).

The power of desktop GIS lies in their unique ability to integrate spatially related information; to manipulate this information with respect to all attributes in addition to locations; to perform simple spatial analysis; and easily to prepare attractive and informative maps or graphs to help display as well as understand spatially related information. They can analyse sites based on drive time, demographic as well as psychodemographic variables, competitive information, and customer information.

Nevertheless, site evaluation requires analytical functions, incorporating forecasts, objectives, costs, and benefits, which are not currently available in GIS packages or model-based functionality add-ins. We also believe that GIS packages do not yet offer the flexibility of spreadsheet tools, favoring loosely coupled approaches. Klosterman and Xie (1997) present a recent example using an adaptation of Huff's (1963) classical retail shopping model. They studied current retail sales patterns in the Akron Ohio metropolitan area and estimated the effect that the opening of a proposed new shopping centre will have on the sales of existing ones. The methodology involved the use of GIS potentialities for mapping exploratory variables for model and results validation.

The previous models can equally be used for existing stores evaluation. Competition aspects can be included using the concept of retail trade area or building forecast models that keep in mind the negative impact of the competing stores in the proximities. However, loosely coupled approaches are commonly slower and less robust software in contrast with strongly coupled customer-written software packages. Complex spreadsheet models can also be harder to debug and understand than conventional programs.

Examples on customer-written software packages based on GIS are present every year in software houses conferences. Two location-related examples are the systems presented by Cowen, Jensen, Shirley, Zhou and Remington (2000). Both are site evaluation models that can calculate comparative values for other locations in the same theme, based on user-selected criteria or gravitational models.

In the last decade, several examples associating decision support models based on regression or spatial interaction models with GIS packages have been reported. Harris and Batty (1993) explore the possibilities of these technologies in planning and location problems, furthermore, recently Birkin, Clarke and Clarke (2002) released a book dedicated to locating retail outlets and network planning using GIS.

One example of a recent decision support system based on GIS is the retail system competition model presented by De Giovanni, Sanlorenzo and Tadei (2003). For the Provincia di Milano in Italy the interaction matrix contains more than two million origin-destination flows. In order to analyse this huge amount of information, including map data as areas around each store (924 stores were considered) like trading areas, demand-zone diffusion areas and store visibility areas a GIS type system was used. This choice supports a user-friendly computer interface and a RDBMS, which allows an efficient evaluation of the model outputs.

Another example has been the decision support systems developed by Tesco plc, described by Attewell (1991). The major use of Tesco's system has been the development of accurate short- and medium-term forecasting models for existing or potential stores. However, the same information system has been used for making decisions, related to the characteristics of the stores to implement in the chosen location, taking advantage of the detailed local collected information decision about the precise location of the store (level tree decisions in Fig. 1).

Conclusion

Retailers have always understood location as paramount. That has been confirmed by recent studies in loyalty and retention (East, Hammond, Harris, Lomax 2000) and by growth of retail geography planning (Birkin, Clarke and Clarke, 2002). But, as Hernández and Bennison (2000) notice, although formal techniques of location analysis have been available for over 50 years, most retailers traditionally make little use of them, relying instead on intuition guided by experience and 'common sense'. However, new circumstances such as the changing retail environment, concentration of market power, the increasing number of demanding costumers, retail trends towards multi-outlet smaller quality shops and evidence of a growing use of GIS make models and quantitative techniques especially relevant.

This paper is a contribution to the review of techniques and models used in multi-outlet site location and turnover assessment. Our intention was not to include every relevant work in such wide field, but to use paramount works to explain the models and methods. The paper is divided into the so-called classical procedures, which are still heavily used nowadays, and newer promising approaches and trends such as the optimal retail location problem and the use of genetic algorithms, Voronoi tessellations in retail trade areas modeling and the use of geographical information systems for site location modeling. Methods and models are explained, practical applications are described and commented and the pros and cons of each one are discussed. The authors also suggest a general framework for the decision levels involved in new outlet location and classify assessment location explanatory variables and factors.

Whichever model and technique is adopted in a particular context, it is important to notice the complexity of store location problems. The number of factors potentially relevant and the dynamic nature of costumer behavior advise several authors as Themido, Quintino and Leitão (1998), Hernández and Bennison (2000), and Birkin, Clarke and Clarke (2002) to underline the 'art and science' nature of retail location decisions. This complexity implies that user past knowledge, subjectivity, and intuition cannot be underestimated in the modeling and systems design as Clarke, Horita and Mackaness (2000) remark. On the other hand, as Birkin, Clarke and Clarke (2002) note, increasing complexity brings greater model accuracy, but only at the expense of a loss of robustness, reduced understanding, and increased cost of implementation and maintenance. The authors feel, derived from our experience in several years of working with the biggest Portuguese retail groups, that an equilibrium between both aspects must be found for every particular application on locational decision-making.

This work is part of an operational research as well as a systems information project where the first aim is to elaborate a GIS-based decision support system for a Portuguese food retailer, which combines several of the reviewed models and techniques (Cardoso and Mendes, 2002; Gonçalves and Mendes, 2002). The decisions to support are essentially store location (type two in Fig. 1), by means of evaluating turnover forecasts in several locations. Variations of the same models are expected to evaluate store characteristics decisions (level three), as the introducing of new services (receiving orders by telephone and Internet, home delivery, between others), product mix, and outlet design.

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